SCIENCE CHINA
Information Sciences

• LETTER •
Special Focus on Pigeon-Inspired Optimization

July 2019, Vol. 62 070211:1–070211:3
https://doi.org/10.1007/s11432-018-9727-y

Generalized pigeon-inspired optimization algorithms

Shi CHENG[1], Xiujuan LEI[1], Hui LU[2*], Yong ZHANG[3] & Yuhui SHI[4]

[1]*School of Computer Science, Shaanxi Normal University, Xi'an* 710119*, China;*
[2]*School of Electronic and Information Engineering, Beihang University, Beijing* 100191*, China;*
[3]*School of Information and Electronic Engineering, China University of Mining and Technology, Xuzhou* 221008*, China;*
[4]*Shenzhen Key Lab of Computational Intelligence, Department of Computer Science and Engineering, Southern University of Science and Technology, Shenzhen* 518055*, China*

Received 12 August 2018/Accepted 30 November 2018/Published online 9 May 2019

Citation Cheng S, Lei X J, Lu H, et al. Generalized pigeon-inspired optimization algorithms. Sci China Inf Sci, 2019, 62(7): 070211, https://doi.org/10.1007/s11432-018-9727-y

Dear editor,

We propose a generalized pigeon-inspired optimization (GPIO) algorithm to enhance the exploitation ability of the original pigeon-inspired optimization (PIO) algorithm. Three variants of the PIO algorithms, including the original PIO, GPIO with ring structure (PIOr), and GPIO with ring structure and simplified landmark operator (PIOrs), are analyzed from a component-wise perspective. To analyze the property of various operators, experimental tests are performed on two types of optimization problems: single-objective and multimodal. The aim is not to compare the performance or effectiveness of various PIO algorithms, but to analyze the properties of different components of the PIO algorithms in addressing different types of optimization problems. Based on the result comparison and component analysis, it can be concluded that different operators of PIO algorithms have various exploration or exploitation abilities during the search. The exploitation ability and diversity of solution maintenance ability should be enhanced for various PIO algorithms in addressing multimodal optimization or more complex engineering problems.

The optimization aims to identify the global best feasible solution(s) for a given problem. Swarm intelligence, including a population of individuals in the search process, is a group of nature-inspired searching techniques [1]. Various swarm intelligence algorithms, such as particle swarm optimization (PSO) [1], PIO [2, 3], and brain storm optimization (BSO) [4, 5], were proposed to solve various problems [6, 7].

The PIO algorithm is a bio-inspired swarm intelligence optimizer based on the collective behavior of pigeons [2, 3]. In the PIO algorithm, each individual represents a potential solution, and this solution is a point in the n-dimensional solution space. The PSO algorithm was modeled on the social behaviors observed in flocking birds [1, 8]. Several differences observed between the PIO and PSO algorithms are as follows.

- The information of previous solutions is utilized in the PSO algorithm, whereas the PIO algorithm only uses the search information of the current solutions. A memory mechanism exists in the PSO algorithm, i.e., the previous information is used to assist the search process.
- The PIO algorithm has two search operators: the map and compass operator and the landmark operator. The individuals are updated with two different strategies and only one strategy in the PIO and PSO algorithms, respectively.
- Both PIO and PSO algorithms have used the individual with the best fitness value to guide the search process. Additionally, the ranking and fitness values of several individuals are used in the landmark operator of the PIO algorithm.

To enhance the exploitation ability of the original PIO algorithm, the GPIO algorithm is proposed and analyzed in this study. The main

* Corresponding author (email: mluhui@buaa.edu.cn)

achievements presented in this study are summarized as follows.

- The GPIO algorithm with different structures and simplified landmark operators is proposed to improve the search ability of the original PIO algorithm.
- The properties of the two variants of the GPIO algorithm, including PIOr and PIOrs, and the original PIO algorithm, are compared and analyzed from a component-wise perspective.
- The comparison of different PIO algorithms on two types of optimization problems is conducted to validate the effectiveness and efficiency of the PIO variants. The optimization benchmark problems involve the single-objective optimization problems with or without shifts in the decision space and the multimodal optimization problems.

GPIO algorithm. The exploration and exploitation abilities are two major factors that affect the optimization algorithm's performance. The exploration ability aims to identify find good promising solutions with high probability by exploring different areas of the search space. In contrast, the exploitation ability aims to concentrate on the search around a promising region and to refine a candidate solution. The original PIO has a rapid convergence speed during the search; however, its fitness value of less than zero is not defined. Hence, the exploitation ability of the original PIO algorithm should be enhanced. The GPIO algorithm, which has three revised operators, is proposed to address these obstacles. The revised operators include generalized topology structure, generalized mapping function, and simplified landmark operator.

- Generalized topology structure. In the map and compass operator of the original PIO algorithm, the swarm has a global star structure, i.e., all individuals are guided to the global optimum. An algorithm with the global star structure has a rapid convergence speed. However, individuals are easily "stuck" in the local optima.

The impact of the previous velocity rapidly decreases with large R. As shown in Figure 1(a) and (b), $\mathrm{e}^{-R\times N_c}$ with $R=0.8$ is close to 0 when N_c is close to 1000 and $\mathrm{e}^{-R\times N_c}$ with $R=0.1$ is close to 0 when N_c is close to 8000. Thus, the parameters R and number of iterations $N_{c_1\max}$ should be set simultaneously.

To balance the exploration and exploitation abilities of the search algorithm, different topology structures are embedded into the GPIO algorithm. Two typical topology structures are used in population-based algorithms. The first one is the global star structure where all individuals are connected with each other; the second one is the local ring structure where each individual has only two neighbors in the swarm. Using different topology structures, the position update equation is revised as follows:

$$V_i^{N_c}=V_i^{N_c-1}\cdot \mathrm{e}^{-R\times N_c}+\mathrm{rand}\cdot (X_{\mathrm{nbest}}-X_i^{N_c-1}),$$

where X_{nbest} is the best position of the current pigeon's neighborhood.

- Generalized mapping function. The mapping function can map the fitness value $\mathrm{fit}(X_i)$ to the weight $F(X_i)$ in the landmark operator of the original PIO algorithm. The original PIO algorithm only defined the situation that $\mathrm{fit}(X_i)\geqslant 0$. For all the individuals in a swarm, if $\forall\, \mathrm{fit}(X_i^{N_c-1})\geqslant 0$, then the definition of $F(X_i^{N_c-1})$ is expressed as follows.

For minimum problems:

$$F\left(X_i^{N_c-1}\right)=\frac{1}{\mathrm{fit}(X_i^{N_c-1})+\varepsilon},$$

while for maximum problems:

$$F\left(X_i^{N_c-1}\right)=\mathrm{fit}\left(X_i^{N_c-1}\right).$$

A generalized mapping function is defined to enhance the generalization ability of the PIO algorithm. If $\exists\, \mathrm{fit}(X_i^{N_c-1})<0$, then $F(X_i^{N_c-1})$ could be expressed as follows.

For minimum problems:

$$F\left(X_i^{N_c-1}\right)=\frac{1}{\mathrm{fit}(X_i^{N_c-1})+|\mathrm{fit}(X_{\min}^{N_c-1})|+\varepsilon},$$

while for maximum problems:

$$F\left(X_i^{N_c-1}\right)=\mathrm{fit}\left(X_i^{N_c-1}\right)+\left|\mathrm{fit}\left(X_{\min}^{N_c-1}\right)\right|,$$

where $|\mathrm{fit}(X_{\min}^{N_c-1})|$ is the minimum fitness value of the current population at the (N_c-1)th iteration.

Simplified landmark operator. In the original PIO algorithm, the number of the remaining individuals is dynamically reduced per iteration. To simplify the landmark operator, it can be a fixed value during the search. This value is defined as half of the population size. Eq. (1) provides a simplified version of the number calculation.

$$N_p^{N_c}=\frac{N_p}{2}. \tag{1}$$

Compared with the original PIO algorithm, the number of the remaining individuals is calculated only once in (1). The computational cost of the fitness value sorting is slightly increased in the landmark operator, but the rest of the individuals can be calculated and implemented easily.

Conclusion. For single objective optimization, the aim is to find a highly accurate solution in

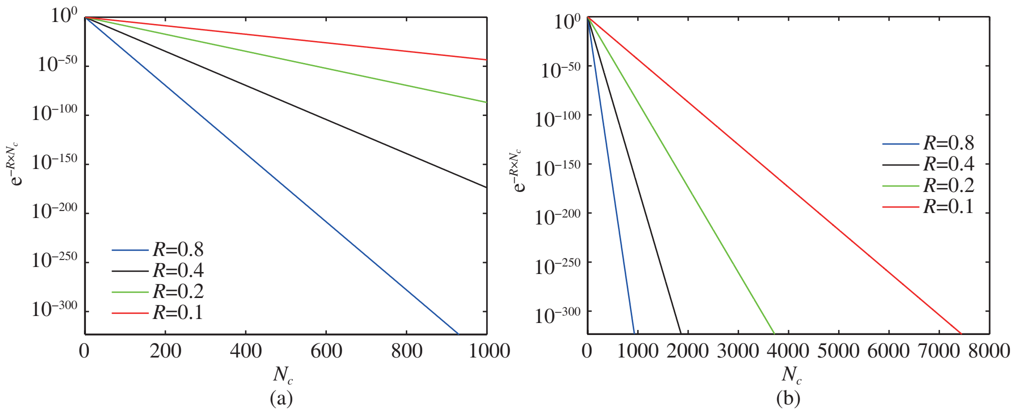

Figure 1 (Color online) Comparison of map and compass operator with different factor settings. (a) $N_c = 1000$; (b) $N_c = 10000$.

limited iterations. While for multimodal optimization, the aim is to locate multiple optima/peaks in a single run and to maintain these found optima until the end of a run. The original PIO algorithm has a good performance on global search ability, however, it performs less well on the solutions maintenance ability. A good algorithm is able to be adjusted for solving different types of problems. In this study, a generalized PIO algorithm was proposed and the properties of different components were analyzed. In an optimization algorithm, different operators have different functions during the search process. To obtain good performances on optimization problems, an algorithm should have an ability to adjust its exploration and exploitation ability during the search.

The experimental study of the three PIO variants (original PIO, PIOr, and PIOrs algorithms) in solving 11 single-objective optimization benchmark problems and eight multimodal optimization benchmark functions are conducted. This study does not aim to compare the performance or effectiveness of various PIO algorithms, but to analyze the properties of different components of PIO algorithms in solving single-objective and multimodal optimization problems. Based on the component analysis and experimental results, it can be concluded that the exploitation ability of GPIO algorithms was enhanced in solving different optimization problems. Moreover, the diversity maintenance ability of the PIO variants should be enhanced to address multimodal optimization problems. Hence, combining the PIO algorithm with other local search strategies is a good approach to improve the search performance of PIO algorithms in solving various complex or multimodal optimization problems. Additionally, two performance criteria are used in the component analysis of the PIO algorithms. To obtain additional search information related to the PIO algorithms in multimodal optimization, more performance criteria should be used in further study.

Acknowledgements This work was supported by National Natural Science Foundation of China (Grant Nos. 61806119, 61672334, 61671041, 61761136008, 61773119, 61771297, 61703256).

Supporting information Appendixes A and B give the experimental results of GPIO algorithm on solving single objective optimization problems and multimodal optimization problems, respectively. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

References

1 Kennedy J, Eberhart R, Shi Y. Swarm Intelligence. San Francisco: Morgan Kaufmann Publisher, 2001
2 Duan H B, Qiao P X. Pigeon-inspired optimization: a new swarm intelligence optimizer for air robot path planning. Int J Intell Comput Cyber, 2014, 7: 24–37
3 Duan H B, Qiu H X, Fan Y M. Unmanned aerial vehicle close formation cooperative control based on predatory escaping pigeon-inspired optimization. Sci Sin Tech, 2015, 45: 559–572
4 Shi Y H. An optimization algorithm based on brainstorming process. Int J Swarm Intell Res, 2011, 2: 35–62
5 Cheng S, Qin Q D, Chen J F, et al. Brain storm optimization algorithm: a review. Artif Intell Rev, 2016, 46: 445–458
6 Zhang Y, Gong D W, Cheng J. Multi-objective particle swarm optimization approach for cost-based feature selection in classification. IEEE/ACM Trans Comput Biol Bioinf, 2017, 14: 64–75
7 Cheng S, Zhang Q Y, Qin Q D. Big data analytics with swarm intelligence. Ind Manage Data Syst, 2016, 116: 646–666
8 Cheng S, Shi Y H, Qin Q D. Population diversity of particle swarm optimizer solving single and multi-objective problems. Int J Swarm Intell Res, 2012, 3: 23–60